Simulation of an Improved Cyclone System by Artificial Neural Network, Adaptive-network-based Fuzzy Inference System and Hybrid ANN-genetic Algorithm Approach

J. Sargolzaei[1], A. Hedayati Moghaddam[*2], M. Alizadeh[3]

Department of Chemical Engineering, Ferdowsi University of Mashhad
Azadi sq., Mashhad, Iran

[1]sargolzaei@um.ac.ir; [*2]amin_hedayati2008@yahoo.com; [3]Mohsen.alizadeh850@gmail.com

Abstract

Simulation of an improved cyclone was carried out by means of Artificial Neural Networks (ANNs), adaptive-network-based fuzzy inference system (ANFIS), and hybrid ANN-Genetic Algorithm (GA). The apparatus consists of two cyclones coupled with a specially designed cylindrical chamber, which includes a rotating tube inside with air-impinging nuzzles drilled on the peripheral surface of the tube. The chamber includes a tube with nozzles on its peripheral surface from which jet-impingement flow throws the particles nearer to wall of the chamber. Efficiency of the jet-impingement chamber, as a function of flow rate on the feed, recycle, jet-impingement along with jet-impingement tube rotational speed, has been tested. ANN, ANFIS, and hybrid ANN-GA are capable to accurately capture the non-linear characteristics of the chamber performance.

Keywords

Dust Removal, Jet-Impingement, Genetic Algorithm, Neural Network, ANFIS

Introduction

Cyclones are used widely to separate dust from air in industries. In cyclones, centrifugal forces are imposed on the particles to stimulate the separation of particles from the gas stream. This force is achieved by rotating the gas stream inside the cyclone chamber. The main drawback of cyclones is the low efficiency in removing fine particles. Thus, many investigations have been conducted to improve the efficiency of cyclones either by the introduction of improved designs or by modifications in the structure of the current equipment (Molerus and Glückler, 1996). In some works, an auxiliary device termed post cyclone (PoC) was introduced to advance the efficiency of cyclones (Jo et al., 2000; Ray et al., 1997). The idea of PoC has been relied on recycling a portion of effluent to cyclone. In this way, another chance would be given to the particles to bear centrifugal forces, in which an especially designed chamber, called recycle dividing chamber, was used to divide outlet gas stream into two streams. The purpose of designing the chamber is to take the benefits of increasing the concentration of particles.

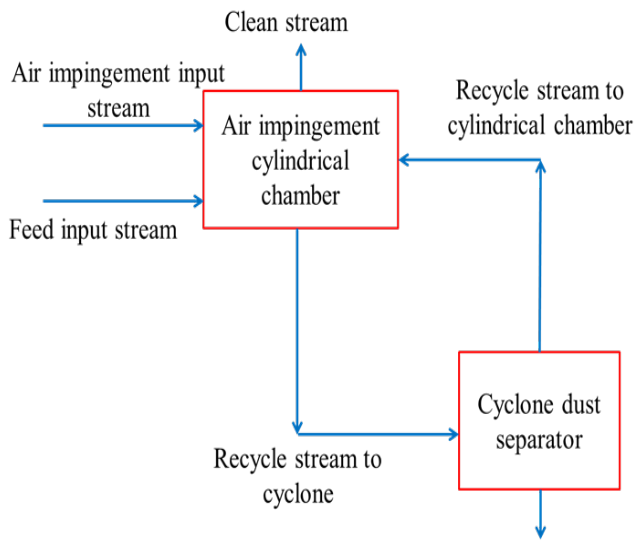

FIG. 1 DUST SEPARATION PROCESS WITH IMPINGEMENT CHAMBER COUPLED WITH A CYCLONE

The diagram of combined system is shown in Fig. 1, in which the dusty feed stream mixing with the recycled stream, passes through the chamber, whereby two streams are formed at the outlet of the chamber.

There are several works employing mathematical model to simulate hydro cyclone performance (Avci and Karagoz, 2000; Hsieh and Rajamani, 1991; Maynard, 2000).

Slack et al. (2000) investigated the simulation of the flow fields of a Stairmand design cyclone by Reynolds

stress model of turbulence and large eddy simulation technique and finally the obtained results were compared with experimental data. They reported that there was an excellent agreement between predicted and experimental data. Bhaskar et al. (2007) tried to simulate water and solid distribution data on different geometries of cyclones using a computational fluid dynamics (CFD) software. They said that the feed inlet pressure would influence the mass flow through the cyclone and also spigot opening has major influence on percent split into the overflow. There are several other works that applied CFD to simulate the cyclone performance (Cullivan et al., 2003; Cullivan et al., 2004; Udaya Bhaskar et al., 2007) but these simulations failed to correctly evaluate the efficiency of cyclones (Altmeyer et al., 2004).

Finding the non-linear relationships between input and output data of a cyclone to develop a mathematical model is a challenging task and in some cases it is impossible due to the complexity of the systems. On the other hand, the application of the numerical methods such as CFD to simulate the process and then optimize the cyclone is time and cost consuming, meanwhile, the prediction ability of this method has not been completely proved. The main practical advantage of intelligent systems over mathematical models and numerical methods is that predictions can be performed in an easy, fast, and accurate way, which is valuable for practical purposes in the design of cyclones.

In this study, the effect of four operative parameters (feed input flow rate, recycle flow rate, jet-impingement flow rate and the rotational speed of the tube nuzzle) on performance of a pilot scale apparatus was simulated by adaptive-network-based fuzzy inference system (ANFIS). In addition, the ability of artificial neural networks (ANNs) to predict the performance of modified cyclone was tested. During training process of an ANN, confronting local minima derived from randomly initial guesses is common, which leads to a huge decrease in prediction ability of this tool. Use of genetic algorithm as an optimization tool to determine the weights and biases would improve the training process (Himmelblau, 2000). Accordingly, a hybrid of ANNs and GA was applied to simulate the performance of improved cyclone, and an extensive comparison was made between the ANNs and hybrid ANNs–GA prediction results as well.

Background

Architecture of Artificial Neural Network (ANN)

ANN is one of the attractive methods to figure out the unpredictable relations between input and output variables in many different processes (Looney, 2002) based on biological neural systems (Bhatti et al., 2011). A neural network is, by definition, a system comprising processing elements called neurons, and a parameter termed weight which is assigned to each neuron, in which all the neurons and related weights are formed. The architecture of the network, the magnitude of the weights and the processing element's mode of operation are the effective parameters that influence the network function. Neuron is a processing element that takes a number of inputs as well as their weights, then sums them up, adds a bias (b) and uses the results as an argument for a transfer function (f). The architecture of a feed forward neural network is shown in Fig. 2 (Wang and Butler, 2001), in which transfer function is assigned to each neuron that determines the value of outputs. Several common types of transfer functions such as sigmoid, hyperbolic tangent and linear would be applied in different conditions.

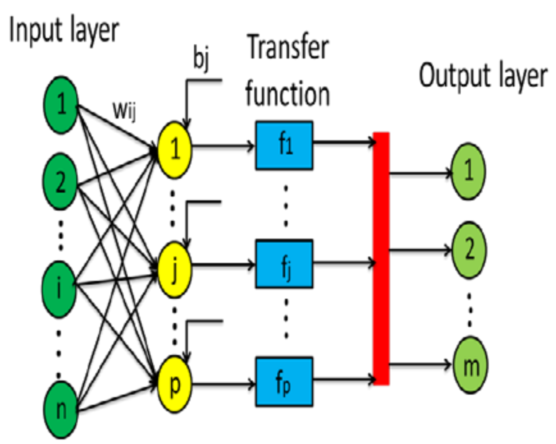

FIG. 2 THE ARCHITECTURE OF THE FEED FORWARD NEURAL NETWORK

Description of Adaptive-Network-Based Fuzzy Inference System (ANFIS)

The main goal of a fuzzy logic system is to reveal input-output relationships that describe the process. ANFIS, a hybrid neuro-fuzzy system, which applies desirable properties and corrects undesirable properties of ANNs and fuzzy logic techniques (Fazilat et al., 2012), has a fuzzy logic context that utilizes a neural network to determine the shape of membership and rule extraction (Iyatomi and Hagiwara, 2004). It is important to note that

description of a process using fuzzy logic consists of two stages: (I) the determination on the input–output space partition and the number of rules that must be used by the fuzzy system and (II) parameter optimization (Pomares et al., 2001; Pomares et al., 2002). In ANFIS, ANN determines and adjusts the parameters and fuzzy rules.

Operation of genetic algorithm (GA)

GA, introduced by John Holland in the 1960s and developed by Holland et. al during 1960s-1970s (Taheri and Mohebbi, 2008), is stochastic search process inspired by natural evolution (Hao et al., 2004) following "survival-of-the-fittest" and "genetic propagation of characteristics", principles of biological evolution (Desai et al., 2008), which is very appropriate for the optimization problems where analytical functions are unobtainable. Using GA starts with the creation of the blind random population defined by the problem at hand (Rajendra et al., 2009). The population of the solution is modified to a new population by the utilization of genetic operators (John et al., 2008).

In general, five steps are performed in GA optimization:

1. The creation of a stochastic initial population of N chromosomes where each string contains l components.
2. The selection of parents for the mating pool (size of mating pool = population size).
3. The shuffle of the mating pool.
4. For each consecutive pair, crossover was applied with probability p_c, otherwise the parents were copied.
5. The application of mutation for each offspring (bit-flip with probability p_m independent of each bit).

The old population was replaced with the resulting offspring, the fittest individuals of every generation (elite), and they would survive in the next generations (Istadi and Amin, 2007) without performing any operations on them (Bhatti et al., 2011).

Hybrid ANN-GA

Hybrid GA and ANN can be good approach to predict and optimize complicated function as well as obtain an optimal or near optimal solutions (Rajendra et al., 2009). The internal relationships between variables found by ANN and GA creates the optimum condition. The hybrid of the two artificial intelligence techniques is utilized extensively (Mirzazadeh et al., 2008). In this approach GA is used to optimize the weights and biases with other fixed ANN parameters.

In genetic learning, weights and biases (input data) are evaluated by designed neural network architecture and then the sets of errors between actual and predicted output vectors are computed. The fitness of an individual simulation is determined by total mean square error (MSE). This process continues until the maximum generation or minimum MSE or the arbitrary user's condition is obtained.

Calculation of Error and Normalized Data

The performance of the neural network model has been evaluated using MSE, average relative error (ARE) and absolute average relative error (AARE). The determination coefficient (R^2) of the simulated and measured data can be expressed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_{\exp.(i)} - y_{pred.(i)})^2}{\sum_{i=1}^{N} (y_{\exp.(i)} - \bar{y})^2} \quad (1)$$

$$MSE = \frac{\sum_{i=1}^{N} (y_{\exp.(i)} - y_{pred.(i)})^2}{N} \quad (2)$$

$$ARE = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{y_{\exp.(i)} - y_{pred.(i)}}{y_{\exp.(i)}}\right) \quad (3)$$

$$AARE = \frac{1}{N} \sum_{i=1}^{N} \left|\frac{y_{\exp.(i)} - y_{pred.(i)}}{y_{\exp.(i)}}\right| \quad (4)$$

where, $y_{exp.}$ and $y_{pred.}$ are experimental and predicted values, respectively, and N is the number of data.

For avoidance from numerical overflows due to very large or very small values; normalization of inputs seems to be necessary. Therefore data are normalized by the following formula:

$$V_N = (1 - \Delta_U - \Delta_L) \frac{V - V_{\min}}{V_{\max} - V_{\min}} + \Delta_L \quad (5)$$

Where V_N is the normalized value of V, V_{max} and V_{min} are the maximum and minimum values of V, respectively. Based on experience, it was found that a better fit will be achieved if Δ_U and Δ_L (small margins) are kept at a value of 0.05 (Bowen et al., 1998; Sargolzaei and Kianifar, 2009).

TABLE 1 EXPERIMENTAL DATA OF FEED FLOW RATE, RECYCLE FLOW RATE AND JET-IMPINGEMENT FLOW RATE

Experiment No.	1	2	3	4	5	6	7	8
Feed flow rate	326.68	334.57	258.03	258.03	347.8	408.21	336.71	414.57
Recycle flow rate	42.7	75.15	93.61	92.74	88.78	86.11	86.11	86.11
Jet-impingement flow rate	63.84	57.14	84.58	100.79	109.3	120.01	95.53	234.84
Efficiency	96.38	96.89	95.92	96.37	95.3	93.83	94.45	93.9

TABLE 2 EXPERIMENTAL DATA OF FEED FLOW RATE, RECYCLE FLOW RATE, JET-IMPINGEMENT FLOW RATEAND THE ROTATION SPEED OF NUZZLE TUBE

Experiment No.	1	2	3	4	5	6	7	8
Feed flow rate	367.62	390.84	371.42	421.23	396.6	365.05	398.85	398.85
Recycle flow rate	179.47	165.29	195.25	165.29	198.24	178.94	208.44	181.59
Jet-impingement flow rate	65.39	99.44	73.93	96.27	72.6	87.66	87.66	87.66
Rotation speed of nuzzle tube	16.6	16.6	51	16.6	51	33.6	33.6	60
Efficiency	97.72	95.56	95.85	95.44	96.71	97.42	96.67	95.76

TABLE 3 RESULTS OBTAINED FROM ANN AND ANN-GA FOR MODELS I AND II

Number of variables	Model	MSE	R^2	ARE	AARE	MAE
4 variables (model II)	ANN	3.68E-06	0.949	7.79E-04	0.0014	0.0014
	ANN-GA	1.23E-06	0.979	6.50E-06	6.09E-04	5.88E-04
3 variables (model I)	ANN	2.72E-05	0.94	9.52E-04	0.0033	0.0031
	ANN-GA	2.36E-05	0.95	1.61E-04	0.0032	0.0030

Experimental Device

A pilot scale apparatus was designed and built for obtained data. Two cyclones of high efficiency Stairmand design with cylindrical diameter equal to 15 cm were used with a jet-impingement chamber diameter of 30 cm and height equal to 165 cm, and 300 nuzzles of 6 mm diameter were used around the nuzzle tube. Some experimental data of flow rate on feed, recycle and jet-impingement are shown in table 1; while the combination of the three parameters along with the rotation speed of nuzzle tube is shown in table2.

Results and Discussion

In this study, 60 tests were conducted to study the variation of three variables on flow rate including feed, recycle and jet-impingement (model I), and 35 tests were conducted to investigate previous three variables as well as the rotation speed of nuzzle tube (model II).

The results of the ANN and ANN-GA prediction were listed in table 3. The value range of the errors approved the acceptability of these two models as well as perfect accuracy of the hybrid ANN-GA models.

The MSE has been calculated for different number of neurons in the hidden layer to find the best number of neurons indicated in Fig. 3 and Fig. 4. In this way, the number of neurons in the hidden layers was changed while the structures were fixed; and then the network was conducted and subsequently MSE of networks were calculated. Using 8 neurons in the hidden layer for four variables (model II) and 20 neurons for three variables (model I) were found to be the optimum conditions.

The feed forward ANN model was learned using back propagation learning function with adjustment on the learning rate at 0.005. A multi-layer feed forward

neural network with one input, one hidden and one output layer was selected to model the process.

In this case, transfer functions were tangent sigmoid for hidden and output layer.

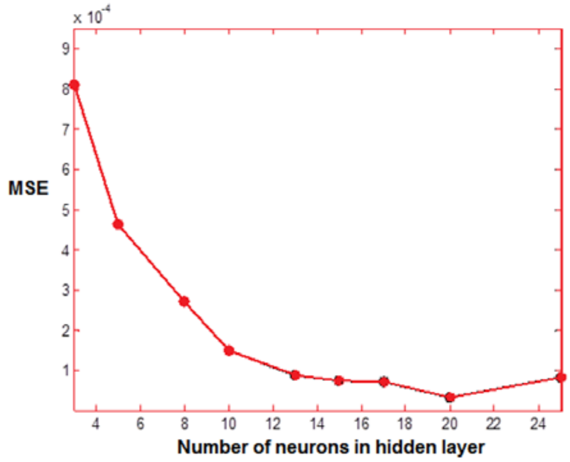

FIG. 3 CALCULATED MSE FOR DIFFERENT HIDDEN LAYERS IN MODEL I FOR ANN SIMULATION

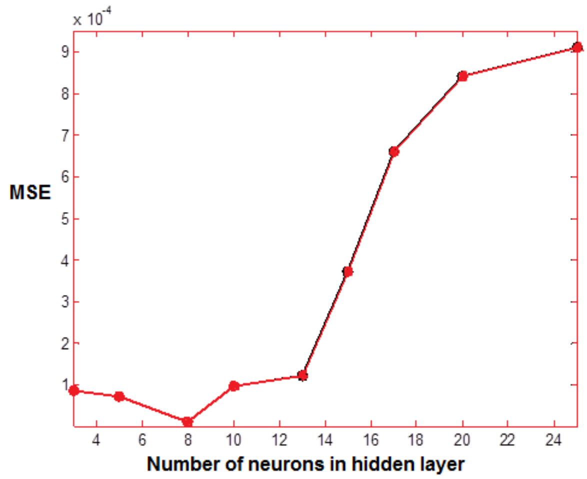

FIG. 4 CALCULATED MSE FOR DIFFERENT HIDDEN LAYERS IN MODEL II FOR ANN SIMULATION

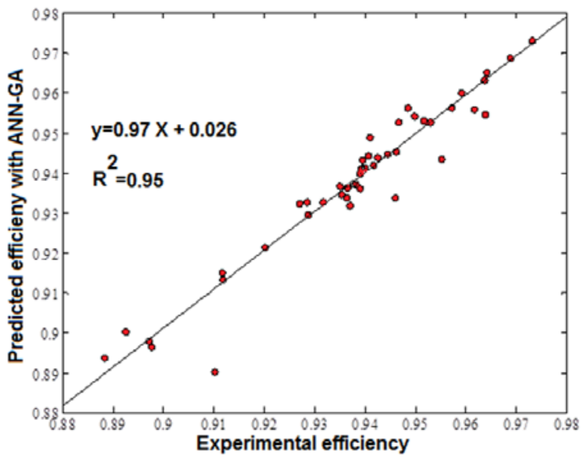

FIG. 5 CORRELATION BETWEEN THE EXPERIMENTAL AND PREDICTED OUTPUT BY ANN-GA IN MODEL

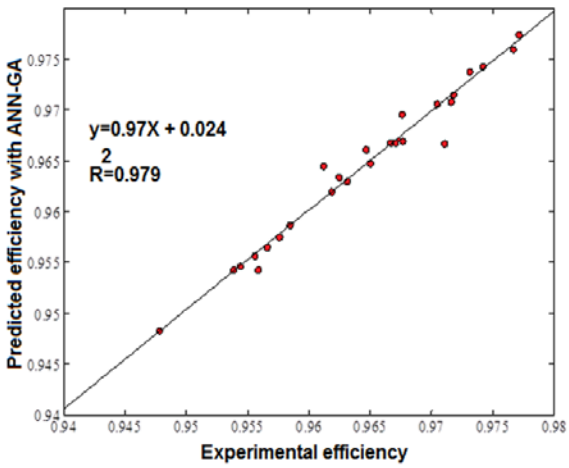

FIG. 6 THE RESULTED CORRELATION BETWEEN THE EXPERIMENTAL DATA AND THE PREDICTED OUTPUT GENERATED BY OUR HYBRID ANN-GA MODEL

TABLE 4 GA PARAMETERS USED FOR OPTIMIZATION IN MODEL I AND MODEL II

Fitness function	**MSE**
Selection method	Roulette wheel
Maximum number of generation	3000
Maximum number of population	20
Probability of crossover	0.65
Probability of mutation	0.05
Elitism percent	0.05

TABLE 5.THE ANFIS INFORMATION USED IN THIS STUDY BY BACK PROPAGATION OPTIMUM METHOD

	Three input variables data	Four input variables data
Number of nodes	78	157
Number of linear parameters	36	75
Number of nonlinear parameters	54	120
Number of training data pairs	23	17
Number of checking data pairs	0	0
Number of fuzzy rules	8	15
Training error	0.019	0.0047
Testing error	0.036	0.027
Epochs optimum	800	2000

For model I, 27 and 8 data were selected as training and testing data, respectively. While for model II, 42 and 18 data were selected as training and testing data, respectively.

The comparison of the experimental output with the predicted output of the ANN for cases I and II was shown in Figs. 5 and 6, which illustrated a good adaption.

In this paper, GA parameters that have been used for optimization were shown in table 4. The parameter, $P_{c,}$ is usually in the range of 0.6 to 0.9($0.02<P_m<0.07$).

The regression of the hybrid models was illustrated in Figs. 5 and 6, which showed a good agreement. The comparison of ANN and ANN-GA results showed the effect of GA in the optimization procedure.

Fig.7 shows hybrid ANN-GA modeling results for efficiency of jet-impingement chamber for model II in three-dimensional perspective.

According to the results, when the feed flow rate is low between 365 m^3/hr and 375m^3/hr with the recycle flow rate more than 190 m^3/h, then the efficiency will be higher. Accordingly when the feed flow rate is high, the percent of the recycle flow rate will decrease and then the performance comes down.

The jet-impingementrate and the efficiency are inversely related and due to the growth of turbulences, the jet-impingement rate efficiency reduces. The best condition for jet-impingement rate range is between 49 m^3/hr and 65 m^3/hr. The effect of the rotation speed of nuzzle tube is negligible.

The best efficiency was 0.9782 on which the flow rate on feed, recycle, jet-impingement together with rotation speed of nuzzle tube were 365.05, 208.44, 49.48,0 respectively that obtained by the genetic algorithm.

Fig. 8 and Fig. 9 show training plot achieved with ANFIS for jet-impingement chamber efficiency with three and four variables input data, respectively. The results of modelling using ANFIS for the jet-impingement chamber efficiency at data set (testing data) are shown in Figs. 10 and 11 for model I and II, respectively. It can be seen that the magnitudes of efficiencies vary significantly with index (data values).

The figures also show that the complex behaviour (non-linearity) of efficiency profile is well reproduced by the ANFIS. As shown in Figs. 10 and 11, there is a well agreement between the output ANFIS and testing data.

The ANFIS information errors used for jet-impingement chamber are shown in table 5. There are 0.5, 1.25, 0.5, 0.15 values for ranges of influence, squash factor, accept ratio, and reject ratio. The best threshold of the generation ANFIS is 0.05 for all jet-impingement chamber simulations.

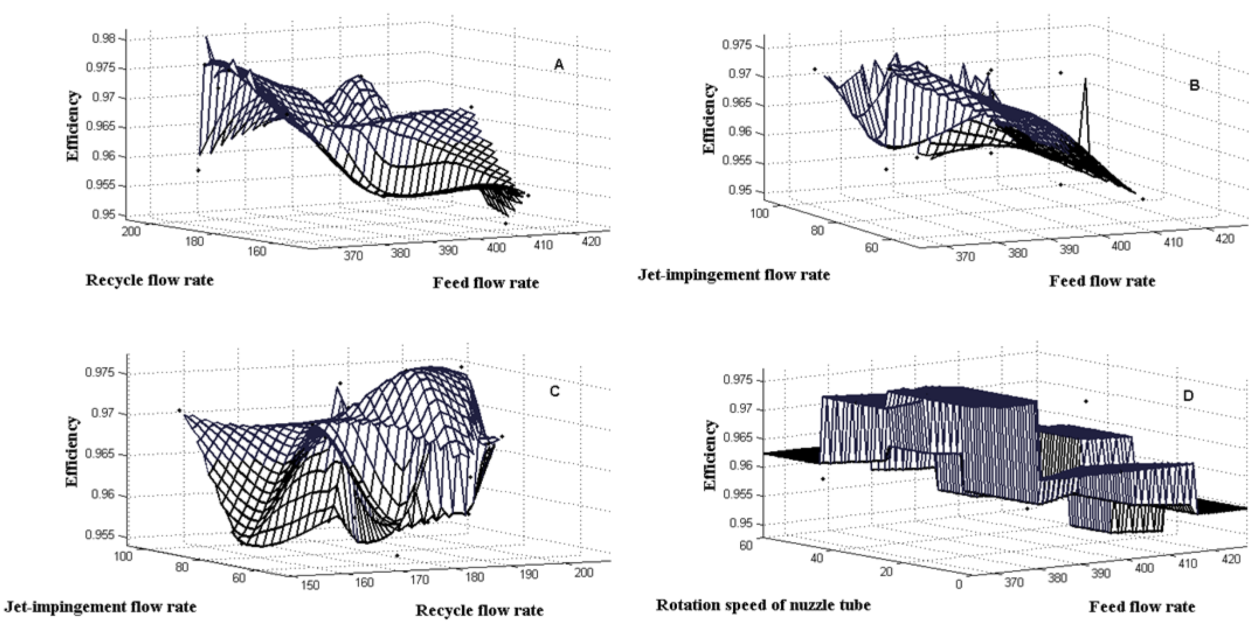

FIG. 7 HYBRID ANN-GA MODELING RESULTS FOR THE EFFICIENCY OF JET-IMPINGEMENT CHAMBER. EFFICIENCY VS. FEED FLOW RATE AND RECYCLE FLOW RATE (A), FEED FLOW RATE AND JET-IMPINGEMENT FLOW RATE (B), JET-IMPINGEMENT FLOW RATE AND RECYCLE FLOW RATE (C) AND ROTATION SPEED OF NUZZLE TUBE AND FEED FLOW RATE (D)

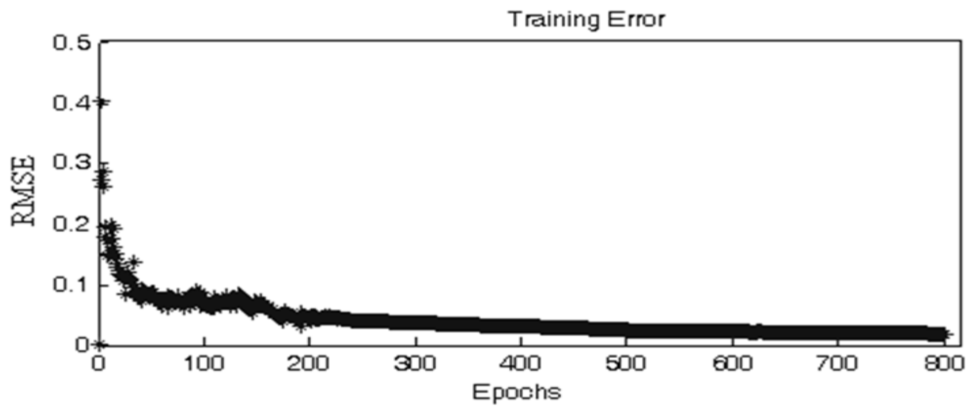

FIG. 8 ANFIS TRAINING RMSE FOR EFFICIENCY OF JET-IMPINGEMENT CHAMBER WITH THREE VARIABLES INPUT DATA

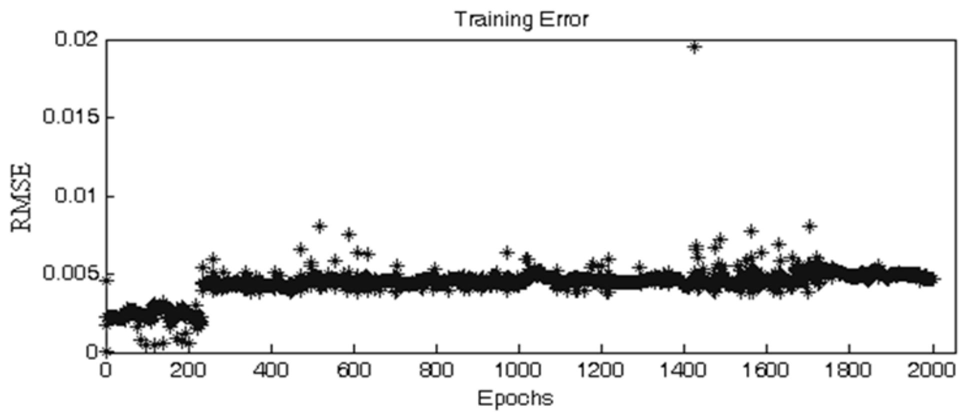

FIG. 9 ANFIS TRAINING RMSE FOR EFFICIENCY OF JET-IMPINGEMENT CHAMBER WITH FOUR VARIABLES INPUT DATA

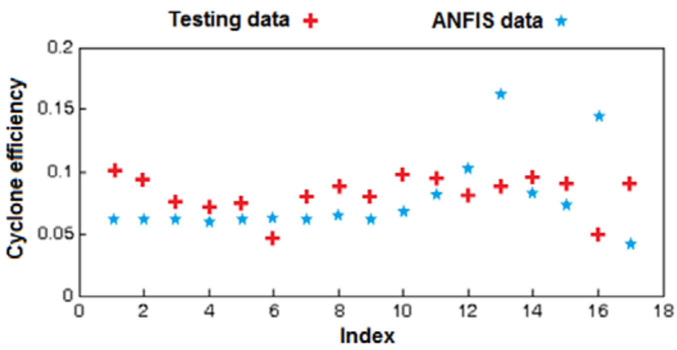

FIG. 10 ANFIS MODELING RESULT FOR EFFICIENCY OF JET-IMPINGEMENT CHAMBER (TESTING DATA) WITH THREE VARIABLES INPUT DATA

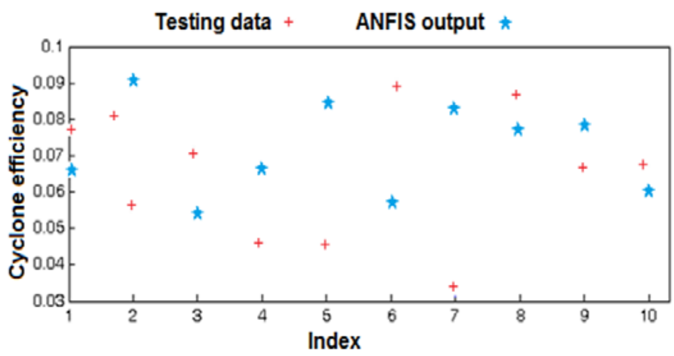

FIG. 11 ANFIS MODELING RESULT FOR EFFICIENCY OF JET-IMPINGEMENT CHAMBER (TESTING DATA) WITH FOUR VARIABLES INPUT DATA

Conclusions

In this paper, an effort has been made to design artificial neural network (ANN), adaptive-network-based fuzzy inference system (ANFIS), and a hybrid ANN-GA to model the efficiency of a jet-impingement chamber system (an improved cyclone). The results of this study show that ANN can be applied as a powerful prediction tool and effective way in simulation and assessment on the performance of a jet-impingement chamber considered in this study. However, GA improved the prediction of process performance. The prediction accuracy of hybrid ANN-GA was better than that of ANN according to our results. Weights and biases have been determined using the GA algorithm to minimize the time and effort required to find the optimal ANN architecture. This means that GA is found to be a good choice instead of the trial and error approach to specify the optimal ANN architecture. According to the results, it can be concluded that when the feed flow rate was high, the percent of the recycle flow rate will decrease and the performance comes down, in addition, the jet-impingement rate and the efficiency were inversely

related; and the effect of the rotation speed of nuzzle tube was negligible.

ACKNOWLEDGMENT

The authors wish to thank the Chemical Engineering Department of Ferdowsi University of Mashhad and the Laboratory of Iran University of Science & Technology.

Nomenclature

AARE	Absolute average relative error
ANN	Artificial neural network
ARE	Average relative error
B	Bias
f^i	Transfer function
FF	Feed forward
GA	Genetic Algorithm
hr	Hour
N	number of data
PoC	Post Cyclone
R^2	correlation coefficient index
Re	Reynolds number
M^3	Cubic meter
MAE	Mean absolute error
Min	Minute
MSE	Mean Square Error
SSE	Standard Sum of Error
V_N	normalized value of V
V_{max}	maximum values of V
V_{min}	minimum values of V
W	Weight
X	input vector
X_i	design factor
y_{obs}	experimental values
y_{est}	estimated values
y_{pred}	predicted values
Δ_U and Δ_L	small margins

REFERENCES

Altmeyer, S, Mathieu, V, Jullemier, S, Contal, P, Midoux, N, Rode, S and Leclerc, J-P 2004. Comparison of different models of cyclone prediction performance for various operating conditions using a general software. Chemical Engineering and Processing: Process Intensification 43: 511-522.

Avci, A and Karagoz, I 2000. A mathematical model for the determination of a cyclone performance. International Communications in Heat and Mass Transfer 27: 263-272.

Bhaskar, K, Udaya, Y, Murthy, Rama, Raju, Ravi, M, Tiwari, Sumit, Srivastava, JK and Ramakrishnan, N 2007. CFD simulation and experimental validation studies on hydrocyclone. Minerals Engineering 20: 60-71.

Bhatti, Manpreet S., Kapoor, Dhriti, Kalia, Rajeev K., Reddy, Akepati S. and Thukral, Ashwani K. 2011. RSM and ANN modeling for electrocoagulation of copper from simulated wastewater: Multi objective optimization using genetic algorithm approach. Desalination 274: 74-80. doi: 10.1016/j.desal.2011.01.083

Bowen, W. Richard, Jones, Meirion G. and Yousef, Haitham N. S. 1998. Dynamic ultrafiltration of proteins - A neural network approach. Journal of Membrane Science 146: 225-235. doi: 10.1016/s0376-7388(98)00108-2

Cullivan, JC, Williams, RA and Cross, R 2003. Understanding the hydrocyclone separator through computational fluid dynamics. Chemical Engineering Research and Design 81: 455-466.

Cullivan, JC, Williams, RA, Dyakowski, T and Cross, CR 2004. New understanding of a hydrocyclone flow field and separation mechanism from computational fluid dynamics. Minerals Engineering 17: 651-660.

Desai, Kiran M., Survase, Shrikant A., Saudagar, Parag S., Lele, S. S. and Singhal, Rekha S. 2008. Comparison of artificial neural network (ANN) and response surface methodology (RSM) in fermentation media optimization: Case study of fermentative production of scleroglucan. Biochemical Engineering Journal 41: 266-273. doi: 10.1016/j.bej.2008.05.009

Fazilat, H., Ghatarband, M., Mazinani, S., Asadi, ZA, Shiri, ME and Kalaee, MR 2012. Predicting the mechanical properties of glass fiber reinforced polymers via artificial neural network and adaptive neuro-fuzzy inference

system. Computational Materials Science 58: 31-37.

Himmelblau, David M 2000. Applications of artificial neural networks in chemical engineering. Korean Journal of Chemical Engineering 17: 373-392.

Hsieh, KT and Rajamani, RK 1991. Mathematical model of the hydrocyclone based on physics of fluid flow. AIChE Journal 37: 735-746.

Istadi, I. and Amin, Nor Aishah Saidina 2007. Modelling and optimization of catalytic-dielectric barrier discharge plasma reactor for methane and carbon dioxide conversion using hybrid artificial neural network--genetic algorithm technique. Chemical Engineering Science 62: 6568-6581. doi: 10.1016/j.ces.2007.07.066

Iyatomi, H. and Hagiwara, M. 2004. Adaptive fuzzy inference neural network. Pattern Recognition 37: 2049-2057.

Jo, Youngmin, Tien, Chi and Ray, Madhumita B. 2000. Development of a post cyclone to improve the efficiency of reverse flow cyclones. Powder Technology 113: 97-108. doi: 10.1016/s0032-5910(00)00206-0

John, Shylu, Sikdar, Sudipta, Swamy, P. Kumar, Das, Sumitesh and Maity, Bhagabat 2008. Hybrid neural-GA model to predict and minimise flatness value of hot rolled strips. Journal of Materials Processing Technology 195: 314-320. doi: 10.1016/j.jmatprotec.2007.05.014

Looney, Carl G. 2002. Radial basis functional link nets and fuzzy reasoning. Neurocomputing 48: 489-509. doi: 10.1016/s0925-2312(01)00613-0

Maynard, Andrew D 2000. A simple model of axial flow cyclone performance under laminar flow conditions. Journal of aerosol science 31: 151-167.

Mirzazadeh, T., Mohammadi, F., Soltanieh, M. and Joudaki, E. 2008. Optimization of caustic current efficiency in a zero-gap advanced chlor-alkali cell with application of genetic algorithm assisted by artificial neural networks. Chemical Engineering Journal 140: 157-164. doi: 10.1016/j.cej.2007.09.028.

Molerus, O. and Glückler, M. 1996. Development of a cyclone separator with new design. Powder technology 86: 37-40.

Pomares, H., Rojas, I., Gonzalez, J. and Prieto, A. 2001. A method for structure identification in complete rule-based fuzzy systems. In A method for structure identification in complete rule-based fuzzy systems, Fuzzy Systems, 2001. The 10th IEEE International Conference on, 376-379: IEEE.

Pomares, H., Rojas, I., González, J. and Prieto, A. 2002. Structure identification in complete rule-based fuzzy systems. Fuzzy Systems, IEEE Transactions on 10: 349-359.

Rajendra, Machavaram, Jena, Prakash Chandra and Raheman, Hifjur 2009. Prediction of optimized pretreatment process parameters for biodiesel production using ANN and GA. Fuel 88: 868-875. doi: 10.1016/j.fuel.2008.12.008

Ray, M.B., Luning, P.E., Hoffmann, A.C., Plomp, A. and Beumer, M.I.L. 1997. Post Cyclone (PoC): An innovative way to reduce the emission of fines from industrial cyclones. Journal Name: Industrial and Engineering Chemistry Research; Journal Volume: 36; Journal Issue: 7; Other Information: PBD: Jul 1997: Medium: X; Size: pp. 2766-2774.

Sargolzaei, J. and Kianifar, A. 2009. Modeling and simulation of wind turbine Savonius rotors using artificial neural networks for estimation of the power ratio and torque. Simulation Modelling Practice and Theory 17: 1290-1298. doi: 10.1016/j.simpat.2009.05.003

Slack, MD, Prasad, RO, Bakker, A and Boysan, F 2000. Advances in cyclone modelling using unstructured grids. Chemical Engineering Research and Design 78: 1098-1104.

Taheri, Mahboobeh and Mohebbi, Ali 2008. Design of artificial neural networks using a genetic algorithm to predict collection efficiency in venturi scrubbers. Journal of Hazardous Materials 157: 122-129. doi: 10.1016/j.jhazmat.2007.12.107

Udaya Bhaskar, K, Murthy, Y Rama, Ramakrishnan, N, Srivastava, JK, Sarkar, Supriya and Kumar, Vimal 2007. CFD validation for flyash particle classification in hydrocyclones. Minerals Engineering 20: 290-302.

Wang, H. and Butler, K. L. 2001. Neural network modeling of distribution transformers with internal short circuit winding faults. In Neural network modeling of distribution transformers with internal short circuit winding faults, Power Industry Computer Applications, 2001. PICA 2001. Innovative Computing for Power - Electric Energy Meets the Market. 22nd IEEE Power Engineering Society International Conference on, 122-127.

Zhou, Hao, Qian, Xinping, Cen, Kefa and Fan, Jianren 2004. Optimizing pulverized coal combustion performance based on ANN and GA. Fuel Processing Technology 85: 113-124. doi: 10.1016/s0378-3820(03)00155-3